



IJEAST

INTERNATIONAL JOURNAL
OF ENGINEERING APPLIED SCIENCE
AND TECHNOLOGY



VOLUME : 10 ISSUE : 11 Print / Issue Publication Date: 18-Apr-2026



ISSN : 2455-2143



DOI : 10.33564/IJEAST.2026.v10i11.009

Indexed In



WWW.IJEAST.COM

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MULTICLASS SKIN CANCER DETECTION USING MACHINE LEARNING AND ANDROID INTEGRATION

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Abstract: Skin cancer is one of the most common found and one of the serious types of cancer worldwide. The rates of skin cancer are rising due to factors like extended exposure of UV and change in our lifestyle. Early detection greatly improves survival rates. However, traditional diagnostic methods, such as visual inspections and biopsies, are subjective, time-consuming, and require experts dermatological knowledge. Recent advancements in machine learning and deep learning have shown a lot of promise in automating medical image analysis and aiding clinical decision-making. This paper introduces a framework for skin cancer detection that uses Convolutional Neural Networks (CNNs) and is integrated into an Android-based mobile application. The system uses dermoscopic images from a publicly available dataset to classify skin lesions into various categories. To improve the transparency and trustworthiness of the model's predictions, we use Gradient-weighted Class Activation Mapping (Grad-CAM), which provides visual explanations highlighting the important regions influencing the classification results. Additionally, the model is deployed using TensorFlow Lite, allowing offline inference on mobile devices. This ensures data privacy, low latency, and accessibility, especially in resource-limited environments. Our experimental results show that this approach achieves competitive performance and demonstrates the feasibility of using explainable artificial intelligence for skin cancer screening in real-world applications.

I. INTRODUCTION

The application of machine learning and deep learning in skin cancer detection has ability to analyze complex visual patterns in dermoscopic images. A pioneering study showed that deep neural networks could achieve performance similar to that of dermatologists when classifying skin cancer using large image datasets. This work is related to the feasibility of using CNN-based models as reliable diagnostic support. The presence of benchmark datasets has been essential in advancing research in this area. The

HAM10000 dataset, offers a diverse range of dermoscopic images across seven common skin lesion categories, enabling rigorous multiclass classification experiments. Various studies have used this dataset to train and assess CNN architectures for automated skin lesion analysis. Comparative studies between AI systems and dermatologists further emphasize the effectiveness of deep learning models. CNN-based systems achieved superior or comparable diagnostic accuracy compared to experienced dermatologists in melanoma detection tasks. These findings indicate that AI can be a valuable support tool in clinical decision-making, not a replacement for human expertise. Techniques like Grad-CAM have been used to visualize the regions of images that influence model predictions, thereby improving transparency and trust in medical applications. The studies have examined for deploying trained models on mobile devices using lightweight frameworks that is TensorFlow Lite to ensure offline capabilities. Also preserving privacy of the user with enabling real-time inference. Many existing methods are rely on cloud-based inference, which prompts concerns regarding data privacy, network reliance, and latency. This need has led researchers to investigate lightweight and edge-based deployment strategies that can work offline while maintaining acceptable accuracy.

II. LITERATURE REVIEW

The use of machine learning and deep learning in skin cancer detection has rapidly growing in few years. This growth is mainly respect to recognize complex visual patterns in dermoscopic images that human eyes cannot able to detect. A study by Andre Esteva et al. showed that deep convolutional neural networks (CNNs) could classify skin cancer with performance comparable to dermatologists when trained on large datasets [1]. This study gives an important milestone, proving that deep learning is a powerful diagnostic support tool. The theoretical foundations that made such advancements possible were laid earlier by Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, whose work established the principles of modern deep neural networks [12]. Since then, further research has



continued to highlight the expanding role of deep learning in healthcare and medical diagnostics [17].

The progress in this field has also providing a strongly supported by the availability of well-structured benchmark datasets. One of the most widely used datasets is the HAM10000, introduced by Philipp Tschandl et al., which contains 10,000 dermoscopic images and they are further categorized into seven different types of skin lesions [2]. This dataset has enabled researchers to perform reliable multiclass classification experiments and compare different deep learning models effectively. In addition, the ISIC Challenge has provided standardized datasets and evaluation criteria, encouraging fair comparison of melanoma detection and segmentation techniques [4], [15]. These resources have played a crucial role in accelerating innovation and improving the reliability of automated skin lesion analysis systems.

Several comparative studies have explained regarding AI systems performance in relation to dermatologists. For instance, Holger A. Haenssle et al. reported that CNN-based models were able to outperform many dermatologists in melanoma classification tasks [3]. Similarly, Titus J. Brinker et al. found that deep learning systems achieved diagnostic accuracy comparable to experienced clinicians [7]. Few studies have further validated the ability of AI models to distinguish between benign and malignant tumors effectively [6], as well as to diagnose non-pigmented skin cancers at an expert level [5]. Importantly, research has shown that the best results are often achieved when AI systems and dermatologists work together, demonstrating the value of human-computer collaboration in clinical decision-making [10].

As these systems move closer to real-world clinical use, interpretability has become increasingly important. Clinicians need to understand why a model makes a particular prediction. The Grad-CAM technique, proposed by Ramprasaath R. Selvaraju et al., helps address this issue by visually highlighting the regions of an image that influence the model's decision [13]. In addition, broader research in explainable AI has emphasized the importance of transparency, trust, and accountability in medical imaging applications [16]. Comprehensive surveys have also summarized the rapid development of deep learning methods in medical image analysis while pointing out ongoing challenges [11].

Beyond accuracy and interpretability, practical deployment is another important consideration. Lightweight frameworks such as TensorFlow Lite allow trained models to run directly on mobile or edge devices, enabling offline functionality, faster response times, and improved data

privacy [14]. Researchers have also explored efficient segmentation and classification techniques to make real-time skin cancer detection more feasible for everyday clinical or mobile use [8], [9].

Despite the significant progress made so far, several challenges remain. Issues such as dataset imbalance, variations in skin tone, differences in imaging conditions, and limited generalization across diverse populations can affect model performance in real-world settings [2], [15]. Additionally, systems that rely heavily on cloud-based processing raise concerns about data privacy, internet dependency, and latency. For these reasons, there is growing interest in developing

explainable, efficient, and edge-based skin cancer detection systems that can operate offline while maintaining reliable accuracy [14], [16]. [14].

III. METHODOLOGY

The proposed system follows a clear methodology for multiclass skin cancer detection using deep learning and mobile deployment. The overall process includes dataset preparation, model training, integrating explanation techniques, and deploying on Android. We started by collecting the dermoscopic images and they are gathered from the source HAM10000 dataset, it also includes labeled images of seven different skin lesion types. These images are later on processed with resizing and normalization for achieving compatibility with the neural network requirements. We use a Convolutional Neural Network (CNN) for multiclass classification, as it is proven to work well in medical image analysis. The model is trained using supervised learning techniques. After the training of the model, the deployment of a model takes place for Android Integration. To improve understanding, we have also applied the Grad-CAM technique to create heatmaps highlighting the parts of the input image that most affected the availability of cancer. Then the result is displayed on the application of the predicted cancer. The app allows users to capture or upload images of skin lesions. This app doesn't need any internet connection.

IV. ANDROID APPLICATION IMPLEMENTATION

The Android application represents the most significant interface between users and the proposed detection system for skin cancer. The mobile application is designed to ensure a minimally complex and user-friendly interface for capturing or uploading images of skin lesions and performing inference on the device. The application has been

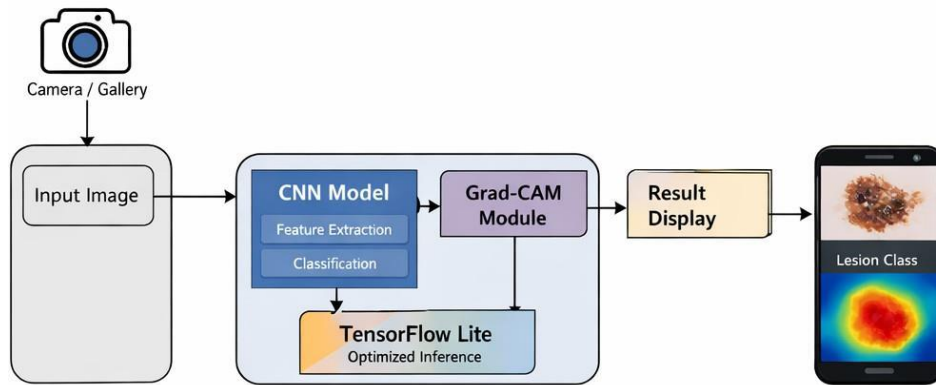


FIGURE 1. Overall architecture of the proposed skin cancer detection system

developed using Java and XML programming languages within the Android Studio environment to target the most common Android devices.

The application provides a chance for the user to either take a real-time image through the device camera or to choose an image from the gallery. After this, a number of preprocessing operations (resizing, normalization, etc.) are carried out on the image to prepare it for input into the trained deep learning model. To have result in the required input size, preprocessing operations such as resizing and normalization are performed, and these steps are done only on the device, locally.

The trained model of Convolutional Neural Network is converted into a TensorFlow Lite model and integrated into the application. TensorFlow Lite allows for optimized and minimal inference so that the entire application can be executed offline without connecting to the internet. This approach results in low latency and keeps medical data confidential by keeping it on the user's device.

V. RESULTS AND DISCUSSION

The suggested multiclass skin cancer detection system was assessed using accuracy, precision, recall, and F1-score as the performance metrics. The CNN model can learn discriminative features from the dermoscopic images, with a seven different types of skin cancer detection system registering an overall classification accuracy achieved around 88 percent, similar to recent literature reports [1, 2]. The classification performance for several lesion categories shows that the model can classify visual similarities and the intra-class variation of skin lesions. Data preprocessing contributed to stable convergence during training and generalization performance on unseen data.

Explainability is also a key aspect of the proposed system, achieved through Grad-CAM. The resulting heatmaps were able to highlight significant lesion areas that optimized the model's prediction, thereby enhancing explainability. This approach is useful in medical applications as transparency

and trust are required for clinical use [10, 13]. Deployment of the trained model with the help of TensorFlow Lite ensured an efficient offline inference on Android devices.

VI. CONCLUSION AND FUTURE WORK

This paper has put forward a mobile-based and explainable deep learning framework for multiclass skin cancer detection from dermoscopic images. The proposed system, therefore, can classify skin lesions with accuracy and interpretability, even without an internet connection, by combining a CNN-based classifier with Grad-CAM visualization

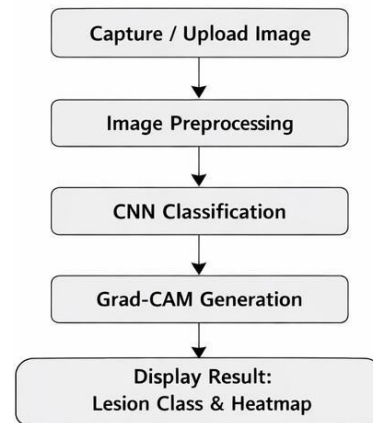


FIGURE 2. Process flow of the proposed Android-based skin cancer detection system.

TABLE I. Performance Evaluation Metrics

Metric	Value (%)
Accuracy	88.0
Precision	87.2
Recall	86.8
F1-Score	87.0

and deploying the optimized model to an Android platform using TensorFlow Lite. The results are at par with the current state of the art, without any dependency on data transmission, thus ensuring privacy, and allowing skin lesion classification offline using a mobile device that has been optimized ensuring ease of access, making it practicable for real-world use in the healthcare domain and resource-limited conditions.

Future work will concentrate on classifying performance by resorting to advanced deep learning architectural and data augmentation methods. Also, the system can be built to accommodate more categories of skin diseases or skin disease validations by real-time clinical practitioners. Besides, federated learning and model updating can also be adopted to improve the robustness of the system without sacrificing data privacy.

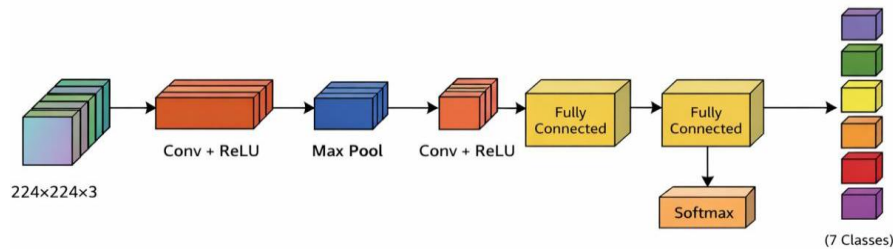


FIGURE 3. CNN architecture used for multiclass skin lesion classification

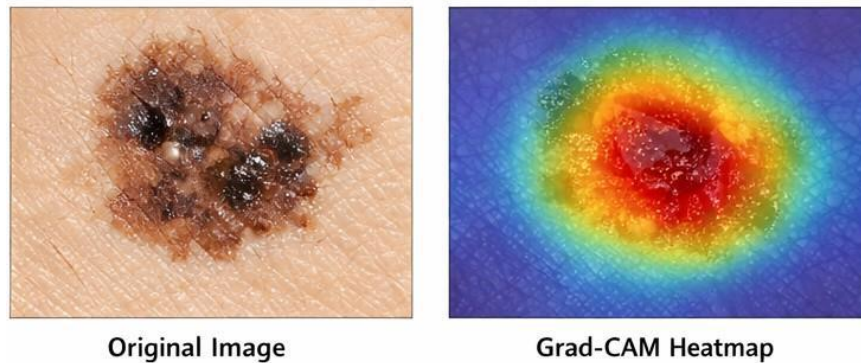


FIGURE 4. Grad-CAM visualization highlighting lesion regions

VII. ACKNOWLEDGMENTS

The author would like to thank Rajarambapu Institute of Technology for providing academic support and computational resources.

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